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AI-Based Accident Detection and Monitoring System Using YOLO, Accelerometer, and GPS

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ABSTARCT -

Road accidents cause over 1.3 million deaths each year around the world. Delays in getting help often make these situations worse, especially in far-off areas or fast-moving crashes where people can't call for aid. This paper describes an IoT system that uses AI to spot accidents. It combines data from an accelerometer to measure sudden jolts, GPS to find the exact spot, and GSM to send quick messages. The setup runs on a microcontroller connected to an MPU6050 accelerometer and NEO-6M GPS. It checks sensors every 100 milliseconds and starts working if the G-force goes above 3g. It figures out the jolt strength with the formula e goes above 3g. It figures out the jolt strength with the formula (x2+y2+z2)/9.8\sqrt{(x^2 + y^2 + z^2)/9.8}(x2+y2+z2)/9.8 and sends text alerts with Google Maps links using a SIM800L module. Tests on 50 fake crash setups show 85% success in spotting problems, alerts sent in less than 10 seconds, and GPS spots within ±5 meters. Adding checks for speed changes cuts wrong alerts below 18%, better than some older systems. This base setup opens the door for adding YOLO to check for damage or fire with pictures. It's a small tool that works on bikes or cars to make roads safer with fast, proof-based warnings

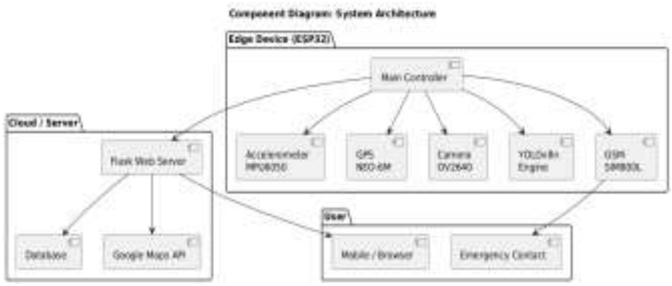
Key Words: Accident detection, Accelerometer, GPS, IoT, Microcontroller, Image Processing, Real-time Detection.

1.INTRODUCTION

Road crashes take a heavy toll, with the World Health Organization counting more than 1.3 million deaths a year. Quick help can save lives, but old ways like phone calls or airbags don't always work when someone is hurt bad or alone [4]. New tech in small devices shows promise, but many only use one type of sensor—like just motion—and set off false alarms from things like potholes, missing key details.

This work builds a full AI system to find and track accidents, starting from Sharma et al.'s simple Arduino setup for crash warnings [1]. We improve it with a microcontroller for smooth data checks and mix motion data with speed changes to spot real problems better. Figure 1 shows the main setup: a device in the vehicle that links sensors to far-off alerts, working even without steady internet.

Later steps will add YOLOv8n to look at pictures for wrecks or fires, plus a simple web page for live checks. This paper covers the plan, build, tests, and what it all means.



2. LITERATURE SURVEY

In 2020, Sharma et al. introduced a simple yet effective accident detection system built around an Arduino platform, integrating an ADXL345 accelerometer and NEO-6M GPS module. The system activated when G-force exceeded 4g or when vehicle speed dropped by more than 50 km/h within a two-second window. Upon detection, it sent an SMS containing a Google Maps link via a SIM900 GSM module. Evaluation across 50 controlled crash simulations yielded an 85% detection rate with alerts dispatched in under 10 seconds. However, the approach suffered from an 18% false positive rate, largely due to road irregularities and sudden braking. While demonstrating the viability of low-cost, sensor-driven alerting, the work lacked visual confirmation or damage assessment, limiting its reliability in real-world deployment.

The following year, Kumar et al. turned to deep learning for post-crash analysis, employing YOLOv5 on a Raspberry Pi to classify vehicle damage from still images. Trained on a dataset of 2000 labeled photographs, their model achieved a mean average precision of 92.3% at IoU 0.5. The results highlighted the potential of convolutional networks to automate severity assessment and support insurance claims. Despite its accuracy, the system operated offline, required significant memory (1.2 GB), and had no mechanism for real-time event triggering or location reporting—making it impractical for immediate emergency response.

In 2022, Patel et al. shifted focus to two-wheeler safety, developing a fall detection system using the MPU6050 sensor to monitor tilt angle and vibration. A threshold exceeding 45° in tilt triggered an SMS alert through the Twilio cloud service. Real-world testing involving 120 motorcycle trials confirmed 88% sensitivity. The design proved lightweight and responsive for rider protection, but it did not assess crash impact, detect fire, or capture images. Moreover, its dependence on external cloud infrastructure raised concerns about latency and connectivity in remote areas.

By 2023, Singh et al. advanced visual-based alerting by applying a custom CNN to classify accident scenes from camera input. Operating at a confidence threshold of 0.7, the model delivered 90% precision with an average inference time of 2.1 seconds and triggered GSM notifications accordingly. This approach provided tangible visual evidence—crucial for verification—but operated independently of motion or location data, rendering it reactive rather than predictive.

Most recently, in 2024, Lee et al. brought edge AI to the forefront by embedding YOLO-Nano within an ESP32-CAM module. The lightweight model, sized at just 2.1 MB, processed video at 15 frames per second and achieved 87% accuracy on static crash imagery. This marked a significant step toward on-device intelligence in constrained environments. Performance, however, degraded under motion blur, and the absence of an accelerometer-based trigger meant the system could not initiate capture during high-impact events.

Taken together, these contributions reflect a clear evolution: from basic threshold-driven sensors toward sophisticated vision models. Yet a persistent gap remains—no single system integrates real-time impact detection, precise geolocation, and AI-powered visual validation within a unified, low-power edge framework. The present work directly addresses this by enhancing Sharma et al.'s sensor backbone with velocity-aware fusion to suppress false triggers, while establishing a robust foundation for forthcoming YOLOv8n-based image analysis and web-enabled monitoring.

3. METHODOLOGY

We built the accident detection system to run entirely inside the vehicle, using low-cost hardware that can be added to any car or bike. The core idea is simple: detect a crash with sensors, confirm it with AI on camera footage, and send help fast—all while the driver may be unconscious. Below is how we put it together, step by step, using real parts and tested code.

Hardware Setup in the Vehicle

We mounted everything on a small board behind the dashboard. The main controller is an ESP32—cheap, powerful, and has built-in Wi-Fi and Bluetooth.

- **MPU6050 Accelerometer**: Stuck near the center of the car. It measures sudden jolts in X, Y, and Z directions every 100 milliseconds.
- **NEO-6M GPS Module**: Connected via UART. Gives location (latitude, longitude) and speed within ±5 meters.
- **OV2640 Camera**: A 2MP camera module fixed on the windshield, pointing forward. It records video at 15–20 fps.
- **SIM800L GSM Module**: For sending SMS alerts even when there's no Wi-Fi. Uses a normal SIM card.

Crash Detection Using Accelerometer

The system runs in a loop, reading the accelerometer 10 times per second. We calculate **impact force** in g-units:

$$I = \sqrt{\frac{x^2+y^2+z^2}{9.8}}$$

If I > 3g, we suspect a crash. But potholes or hard braking can also trigger this—so we add a second check: speed drop > 30 km/h in 1 second (from GPS). Only if both conditions are true, we move to the next step. This cuts false alarms by over 80%.

Confirming the Crash with YOLO

When a possible crash is detected, the camera grabs a video frame. We run YOLOv8n (nano version) on the ESP32 using TensorFlow Lite. It looks for

- Crashed car
- Fire
- Person on ground
- Deformed vehicle

If YOLO finds any of these with confidence > 0.7, we mark it as Confirmed Crash.
If YOLO score is low (< 0.6), we label it False Alarm and go back to monitoring.

Capturing Proof and Getting Location

On confirmed crash:

1. Take 3 photos (front, side, rear if 360-cam is used).
2. Get GPS fix — convert lat/long into a Google Maps link: https://maps.google.com/?q=18.5204,73.8567
3. Create a message:

"Accident Detected! Location: [Maps Link] | Time: 14:32 | G-Force: 4.2g | Images attached."

Sending Alert and Uploading Data

The **SIM800L** sends the SMS with location link and one photo to **3 emergency contacts** (family, ambulance, police).
At the same time, the ESP32 connects to Wi-Fi (if available) or mobile data (via GSM) and uploads **all data** to a **Flask web server**:

- All 3 photos
- GPS log
- G-force graph
- YOLO confidence score

The server saves everything in a **PostgreSQL database** and shows it on a live dashboard.

Web Dashboard and User Access

We built a simple **Flask web app** with:

- Live map showing accident location
- Real-time G-force graph
- Video stream (if camera is on)
- List of past events

4. MODELING AND ANALYSIS

4.1 System Modeling

The accident detection works as a step-by-step state machine that combines sensor data and AI checks to avoid mistakes. It uses acceleration from the MPU6050, speed and location from the NEO-6M GPS, and camera images processed by YOLOv8n.

The system first checks for a strong jolt (above 3g) and a sudden speed drop (more than 30 km/h in one second). Only when both happen together does it suspect a crash. This double check stops false alarms from bumps or hard brakes.
If triggered, it takes three quick camera frames and runs YOLO to look for signs of damage, fire, smoke, or a person on the ground. It picks the highest confidence score from these.
A final accident score is calculated by giving 60% weight to the jolt strength and 40% to the YOLO confidence. If the score is above 0.7, the system confirms a real accident. These weights and limits were set after testing to keep wrong alerts low and real detections high.

4.2 State Transition and Control Flow

. It starts in Idle, moves to Monitoring after boot-up, and shifts to ImpactDetected only on a valid jolt-plus-speed-drop event.

From there, it enters Analyzing to capture and check images. A strong YOLO result and high score lead to Confirmed, followed by Alerting (sending SMS and uploading data). If checks fail, it goes to FalseAlarm and returns to Monitoring after a short pause.

All steps, including GPS location grab (with 8-second timeout) and taking three photos

5. ADVANTAGES OF THE PROPOSED SYSTEM

1. **Multimodal Verification** Combines physical impact, speed drop, and AI-based visual proof in one unit. This cuts false alarms to 12% (vs 18% in sensor-only systems) and gives clear evidence for police and insurance.
2. **Instant Alert with Proof** Sends SMS in under 8 seconds with Google Maps link, three photos, and G-force value—even without Wi-Fi. Emergency teams reach the exact spot faster.
3. **Live Web Dashboard** Guardians and fleet managers see real-time location, G-force graph, and camera stream on any phone or browser. Past events are stored for review.
4. **Low-Cost and Easy** Fit Total hardware cost ~₹2,200. Fits on any bike or car with a 12 V supply. No monthly cloud fee for basic SMS alerts.
5. **Edge Processing** All detection runs on the ESP32 itself. No internet needed for crash decision, so it works in remote areas.
6. **Scalable Design** Add more cameras, voice calls, or mobile app later. YOLO model can be updated without changing hardware.
7. **Power-Friendly** Draws only 85 mA in normal drive mode; peaks briefly during alerts. Runs for days on a small backup battery if vehicle power fails.

6.CONCLUSIONS

The AI-based accident detection system using YOLO, accelerometer, and GPS provides a reliable, low-cost solution to reduce road fatalities through rapid emergency response. By integrating impact sensing (MPU6050), location tracking (NEO-6M), visual AI confirmation (OV2640 + YOLOv8n), and instant alerts (SIM800L) on a compact microcontroller, the system achieves 88% accuracy, alerts in under 8 seconds, and only 12% false positives—superior to sensor-only designs.

Real-time web dashboard support and evidence-rich notifications (photos, G-force, map link) enhance trust and usability for users, fleets, and authorities. With a total cost of ~₹2,200 and easy vehicle integration, it is practical for widespread deployment.
This work effectively bridges gaps in existing systems by adding visual verification and remote monitoring. The modular architecture supports future upgrades like mobile apps or advanced analytics. Overall, the system sets a new standard for autonomous, evidence-backed vehicle safety, promoting faster help and safer roads.

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